



# Aging based optimal scheduling framework for power plants using equivalent operating hour approach



Tarannom Parhizkar<sup>a,b</sup>, Ali Mosleh<sup>b</sup>, Ramin Roshandel<sup>a,\*</sup>

<sup>a</sup> Department of Energy Engineering, Sharif University of Technology, Tehran, Iran

<sup>b</sup> B. John Garrick Institute for the Risk Sciences, UCLA, Los Angeles, CA 90095, USA

## HIGHLIGHTS

- An aging based optimal scheduling framework is developed.
- Operating conditions and maintenance intervals are optimized simultaneously.
- Aging cost is considered in the objective function.
- Equivalent operating hour approach is proposed to address component aging effects.
- Results show 4% higher annual profit for a gas turbine power plant.

## ARTICLE INFO

### Keywords:

Aging based optimal scheduling  
Equivalent operating hours (EOH)  
Operating conditions  
Maintenance intervals  
Power plants  
Gas turbine

## ABSTRACT

In this paper a scheduling optimization framework is developed to enhance power plants operational decision making process. The proposed framework optimizes plant schedule including operating conditions and maintenance intervals simultaneously and on an hourly basis. In a long term operation plant performance deteriorates due to components aging. This study employs equivalent operating hour (EOH) approach to describe components aging impact on the plant performance deterioration and consequently plant long term profit. Modeling of components aging increases system simulation accuracy in long term operation and the optimum decision variables would be more reliable and realistic.

Validity and usefulness of the proposed methodology are demonstrated by optimizing the operating conditions and maintenance intervals of a gas turbine power plant, under different seasonal ambient conditions and energy prices. The case study results effectively meet all the positive expectation that are placed on the proposed aging based optimal scheduling framework. Results show that optimal operation schedule depends on the maintenance intervals. Therefore, operating conditions and maintenance intervals should be optimized simultaneously. In addition, derived optimal schedule increases the system's long term profit approximately 4% annually in comparison with a case that operates at optimal schedule without considering the aging effects in the optimization procedure.

## 1. Introduction

### 1.1. Motivation

Besides using high-tech components in power plants, plant operation optimization can significantly improve energy efficiency and economic performance, as efficiency of plant components generally depends on operating conditions. In addition, system preventive maintenance can reduce plant operation and failure costs, however it is also costly when done frequently. Therefore, optimizing operating conditions and preventive maintenance intervals can minimize the

expected total cost of plant due to operation, failures and preventive maintenances.

In recent years, the use of optimization models to determine plant optimal schedule has earned popularity as in [1]. Scheduling is widely used to maintain and establish operating conditions and maintenance intervals of a plant over time. It should be noted that power plant components are degraded through long term operation [2]. Therefore, components performance profile over time varies. To have a reliable and accurate scheduling optimization results it is necessary to consider components aging models in the optimization procedure. The effect of considering degradation mechanisms in the optimization procedure is

\* Corresponding author.

E-mail addresses: [Parhizkar@sharif.edu](mailto:Parhizkar@sharif.edu) (T. Parhizkar), [Roshandel@sharif.edu](mailto:Roshandel@sharif.edu) (R. Roshandel).

**Nomenclature**

$\alpha$	temperature correction factor of $p$
$\alpha'$	temperature correction factor of $hr$
$\beta$	steam injection correction factor of $p$
$\beta'$	steam injection correction factor of $hr$
$\delta$	load correction factor of $p$
$\delta'$	load correction factor of $hr$
$\eta$	efficiency
$\lambda$	aging correction factor of $p$
$\lambda'$	aging correction factor of $hr$
$A$	ambient condition
$C$	cost
$C^a$	levelized aging cost
$C^f$	fuel cost
$C^h$	heat price
$C^m$	maintenance cost
$C^p$	electricity price
$d$	day number
$dP^{det}$	performance deterioration
$EOH$	equivalent operating hour
$EOH^f$	failure EOH
$F$	fuel consumption
$h$	useful output heat
$hr$	heat rate
$HR^0$	heat rate standard value
$I$	model input

$k^1, k^2$	water/steam injection severity factor
$mf$	maintenance factor
$mf^1$	maintenance factor of combustion inspection
$mf^2$	maintenance factor of hot gas path inspection
$mf^3$	maintenance factor of rotor inspection
$m_s$	steam percentage to compressor inlet air flow
$O$	model output
$op$	operating condition
$op^l$	operating condition lower band
$op^u$	operating condition upper band
$p$	output power
$P$	system performance
$P^0$	base load output power
$R$	income
$S$	load severity factor
$S$	operating schedule
$t$	hours of system operation
$T$	temperature
$z$	long term profit

**Subscripts**

$i$	hour
$j$	month
$k$	year
$m$	maintenance type

investigated in [3] and the degradation based optimization (DBO) concept is introduced [3]. The combination of plant optimal scheduling and aging models is an extended approach that is presented in our study and a framework is developed. The proposed framework optimizes plant schedule over long term horizon considering components aging. The framework outputs determine the plant startup time, production level and maintenance intervals. This framework can be used in the sensitivity analysis of energy price and ambient conditions as well (see Fig. 1).

**1.2. Literature review**

Several current research address power plant scheduling without considering plant aging [4–6]. In these studies, mathematical approaches for optimizing power plant schedule according to different ambient conditions (temperature, humidity, ...), system characteristic

and economic assumptions (energy and fuel prices, and fluctuating energy sale prices) are available.

Other studies have developed aging models that estimate long-term power plant aging and performance deterioration. Aging models of power plant components is a well-developed field [7–9]. However, little emphasis has been placed on combining operation scheduling optimization and plant aging models.

Related pioneering works which introduce plants performance deterioration into scheduling, are described in [10,11]. These references focus on considering the effects of operation conditions on system maintenance interval and failure rate. In [12], the intention is to compute power plant equivalent operating hours (EOH) that determine component aging and performance deterioration under standard operating conditions. This concept is very appealing, however, specific dynamic lifetime scheduling model is not developed. In our study, the framework for a hybrid approach, considering performance

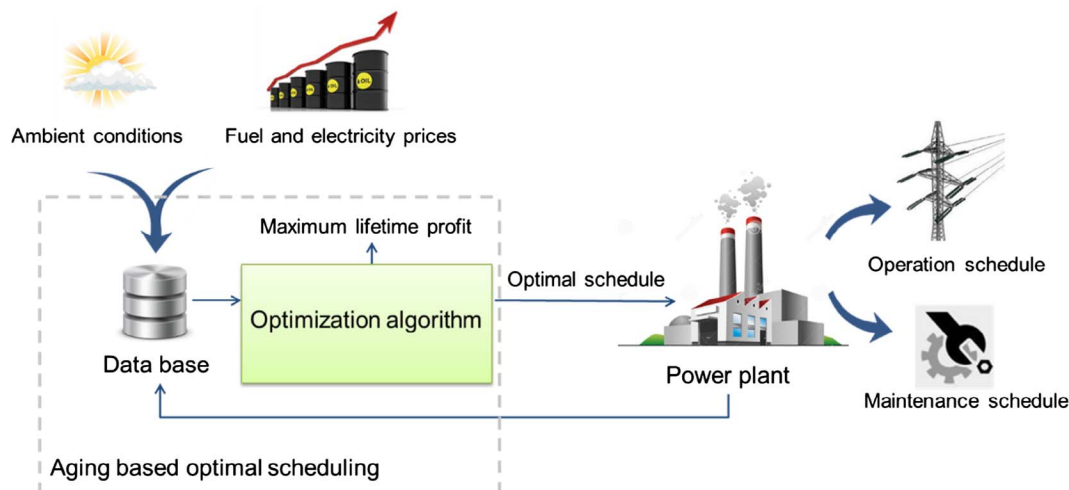


Fig. 1. Data flow schematic of aging based optimal scheduling.

deterioration in operation scheduling is developed to have a large impact on a power plant's economic performance.

The proposed framework, is utilized to cope with the problem of hourly operational management of power plants that exchange electrical energy with the grid, whose prices change hourly and day by day. Hourly long term optimization makes the optimization procedure more complex. Several optimization algorithms of scheduling can be found in literature [13,14]. In [15] linear model is developed and hourly optimum operating conditions are derived based on two stage optimization procedure. Time horizon at the first stage is hourly and then at the second stage is monthly. Many of the studies use linear approximations to describe inherently non-linear energy conversion processes [16,17], while others overcome this approximation through non-linear and mixed integer non-linear programming [18,6,19,20].

As can be concluded from the reviewed literature, most of the reviewed literatures did not consider the component aging effects in the scheduling optimization procedure. In addition, most of the studies focus on the operation scheduling or maintenance intervals optimization, while none of them has considered the interaction of these two aspects simultaneously.

### 1.3. Paper contributions

The major novelties of this study include the following:

- One of the main novelties of the proposed framework is the consideration of aging effects in the optimization procedure. The components aging can result in performance deterioration and system failure. The rate of aging process depends on many factors including operating conditions, system characteristics and period of operation. Effective management of components aging is a key element of the efficient and reliable operation of plants. The developed framework manages aging process by optimizing system's schedule in order to maximize the lifetime profit.
- An improved EOH approach is used in order to address components aging effect on plant performance deterioration. This new approach results in more accuracy in long term simulation and more reliable and realistic plant optimal schedule.
- The developed aging based optimal scheduling framework considers aging cost in the objective function as well as components aging in the optimization procedure. Aging cost is defined as the hourly

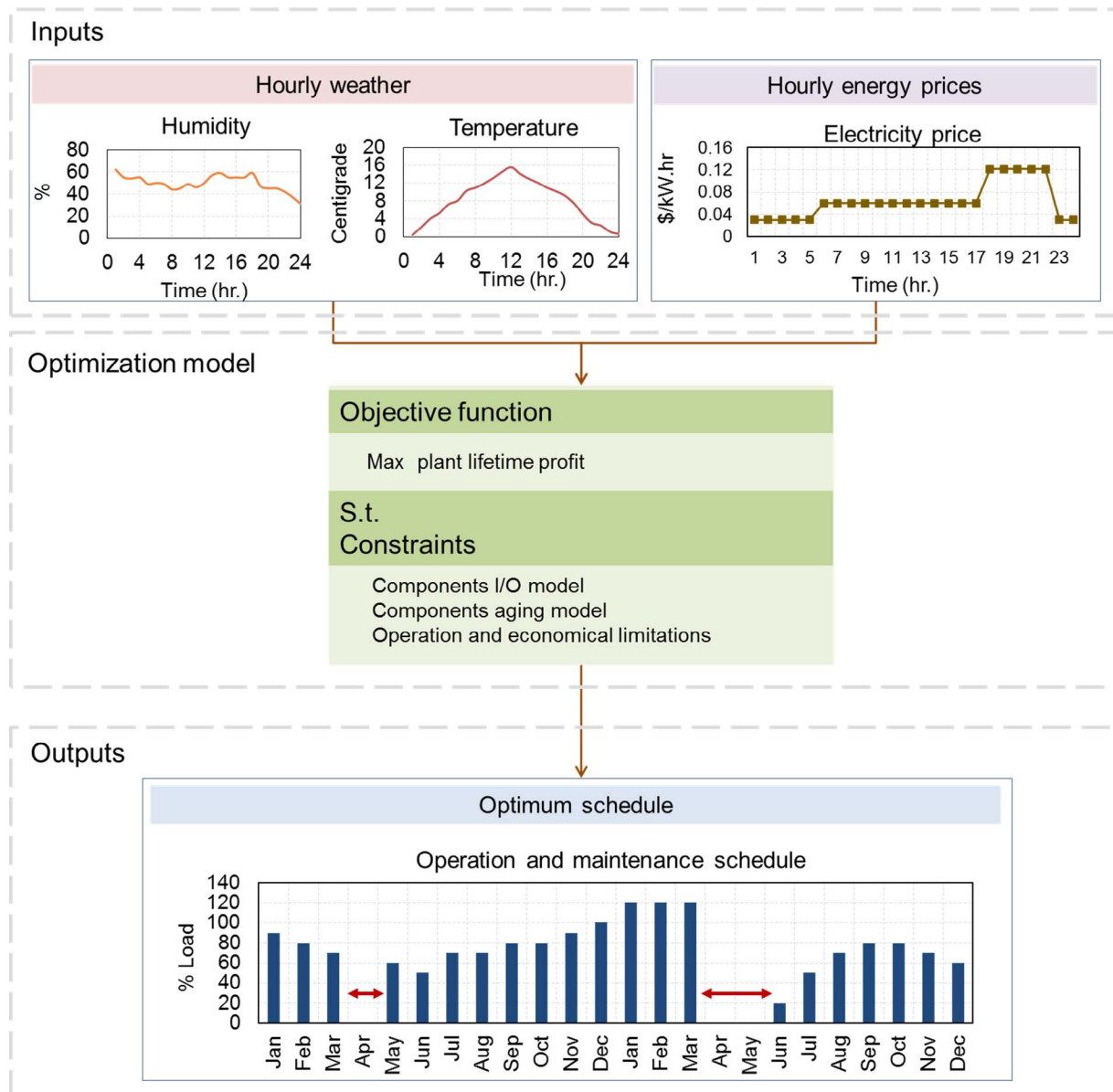


Fig. 2. Integrated framework of aging based optimal scheduling.

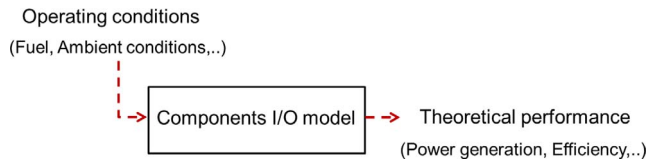


Fig. 3. An I/O model flow data.

- preventive and corrective maintenance costs. As a result, optimal hourly schedule is affected by not only the income of selling electricity and operation cost but also the maintenance cost. Therefore, plant hourly profit is more realistic and the optimal schedule has a higher lifetime profit in comparison with other scheduling methodologies such as day-ahead method.
- The objective of the proposed framework is to find system optimal schedule on an hourly basis in long term operation that is a new approach in schedule optimization. The model inputs such as ambient conditions, fuel and electricity price varies on an hourly basis and consequently optimal schedule will change hourly in long term.
  - The proposed framework produces optimal maintenance and operation intervals of power plants simultaneously. As maintenance intervals and operation schedule are interrelated, the model optimizes both decision variables simultaneously and optimum operation and maintenance intervals schedule will be derived at once.
  - In order to optimize plant hourly schedule and maintenance intervals, an innovative two stage optimization algorithm is proposed. The proposed heuristic algorithm is the hybrid of gradient search method and branch-and-reduce optimization navigator (BARON) method. The low computation time of this method allow concluding that this new optimization algorithm has a high performance in scheduling problems.
  - In addition, a 9F.05 model of general electric (GE) gas turbine power plant is modeled in this study. The hourly optimal schedule and maintenance intervals over 15 years of operation is derived for this power plant. Results show the effectiveness of the proposed framework and solution algorithm.

#### 1.4. Paper organization

The paper is organized as follows: A brief overview of the developed framework is introduced in Section 2. The framework modeling and formulation are presented in Section 3. In Section 4 the optimization algorithm is fully described. Section 5 presents the characteristics and model of the system under study. In Section 6, the results of the case study are discussed, and finally conclusions and contributions are drawn in Section 7.

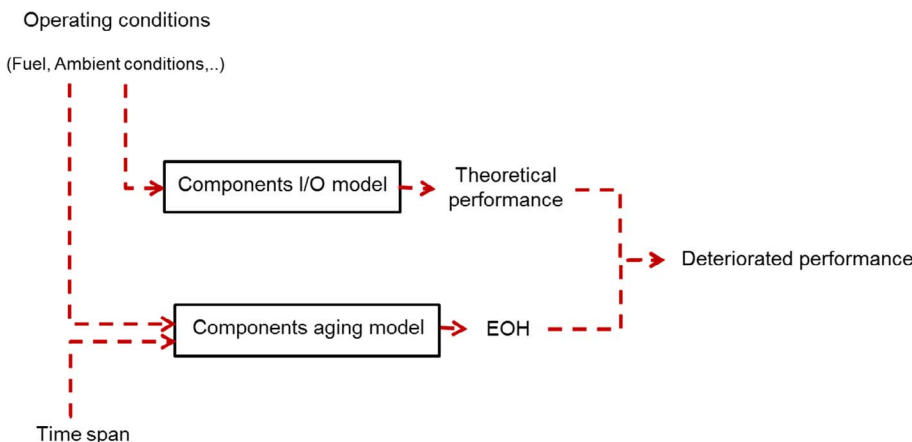


Fig. 4. Flow data of I/O and aging models integration.

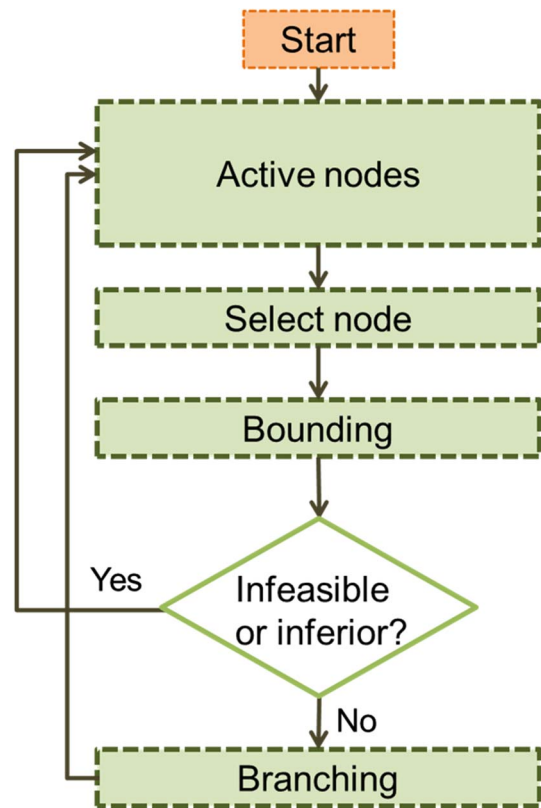


Fig. 5. BARON method algorithm.

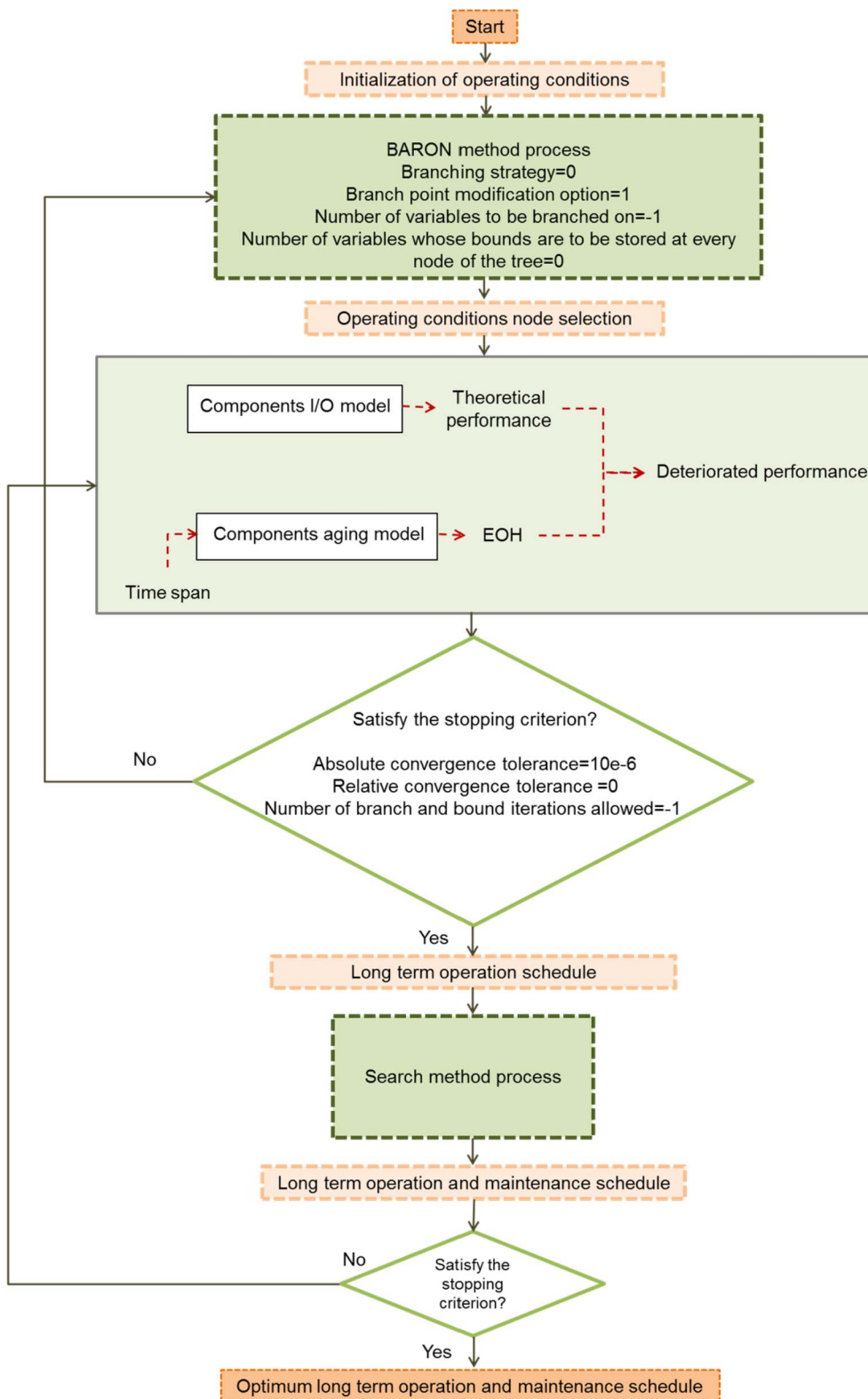
## 2. Aging based optimal scheduling framework

### 2.1. General description

The proposed approach aims at deriving maximum profit schedule that meet power plant operational and economic constraints. This approach considers the plant performance deterioration due to aging effects in the optimization procedure. Therefore, an aging based optimization framework is proposed, that offers a comprehensive representation of the main factors of aging processes in power plants.

Aging based scheduling model is categorized as a dynamic non-linear programming model. Such a model consists of three main elements: (1) an objective function, expressing the power plant lifetime profit to be maximized; (2) constraints, equality and inequality equations expressing the power plant limitations and logical relationships that must be satisfied; and (3) decision variables, the unknown schedule to be determined by the optimization.

Fig. 6. Optimization algorithm of aging based optimal scheduling.



The objective function of the model is to maximize power plant lifetime profit. Profit is defined as income from selling power plant products such as electricity and heat, minus system total costs including fuel and aging costs. The aging cost is the hourly maintenance cost of the system as a function of plant schedule.

Several constraints must be satisfied in the optimization procedure. The equality constraints are mostly the technical governing equations

of the power plant components and processes. The inequality constraints are the economical and operational limits of the plant.

The decision variable of the model is system schedule that includes system operating conditions and outage plan of the power plant. Other main model outputs are plant hourly profit, income and costs including fuel and maintenance cost, as well as hourly and accumulated plant performance deterioration.



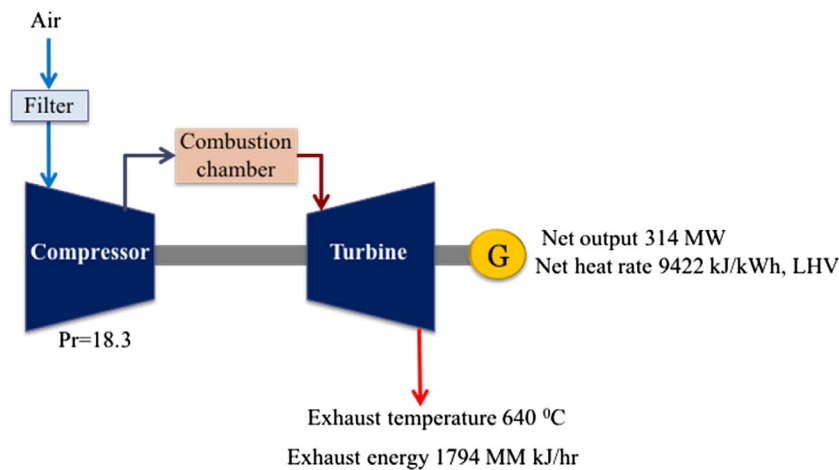


Fig. 7. Gas turbine flow diagram.

**Table 1**  
Technical characteristics of the studied gas turbine.

Manufacturer	Model	Power output	Heat rate	Nominal speed	Cost
–	–	MW	kJ/kWh	rpm	\$/kW
GE	9F.05	299	9295	3600	183.14

Finally, the modified BARON global optimization algorithm is proposed to derive optimal plant schedule that maximize the objective function while respecting all the model constraints. The solution methodology was explained in more detail in the revised manuscript as well.

## 2.2. Flaw diagram

The flaw diagram of the aging based optimal scheduling framework is shown in Fig. 2. The framework determines optimum hourly operation and maintenance schedules based on the hourly weather, hourly energy prices, and operational/economic constraints.

The optimization model is the main part of the framework that consist of two main models. The components input/output (I/O) model focuses on system performance and efficiency. The component aging model considers the updates of system characteristic due to degradation mechanisms which is correspond to the operating conditions.

To consider the effect of operating condition variations on performance deterioration, the maintenance factor and EOH concepts are introduced [12]. conditions and full load operation without steam injection. In this approach, a baseline condition is defined for a component that operate at its baseline conditions. For instance, in a gas turbine plant the baseline conditions are standard ambient. The maintenance factor for baseline conditions is equal to one. At different operating conditions, maintenance factor is used to determine the increased level of required maintenance. Actually, the maintenance factor shows the impact of different operating conditions on system aging and consequently system maintenance intervals. The maintenance factor value is obtained from system historical data [21]. The sum of the hourly maintenance factors determines the actual age of a system that is known as EOHs [22]. Performance deterioration is a function of system actual age that can be derived from engineering experience and system historical data [23]. In fact, EOH concept helps to show the operating condition effect on system aging consequences such as performance deterioration and maintenance costs.

## 3. Problem formulation

### 3.1. General description

Scheduling is essentially a multidisciplinary task involving system performance, operations, maintenance, reliability, economics, and environment dynamics [24]. Many of these factors must be considered in the modeling to have a comprehensive scheduling optimization model. This paper focuses on the performance, operations, and economic factors that affect the power plant profit. The scheduling model optimizes operation and maintenance intervals of a power plant in order to achieve maximum power plant lifetime profit. In addition, components aging is a crucial factor in maximizing the profitability of power plants in long term [3], that is considered in the optimization procedure. In this section, the formulation of the proposed framework is described in detail. The section begins with the introduction of the model inputs and outputs. Then the formulation of the objective function is proposed, afterward the various constraint families are developed.

### 3.2. Model inputs and outputs

Three major external factors are the fuel cost, electricity price, and ambient conditions which are the dynamic factors over time and have impact on the final optimal solution. These parameters are functions of hourly, monthly and yearly time scales and are stochastic in nature. However, the trend of these parameters are important in long term scheduling that is deterministic. For instance, the price of electricity is higher in peak hours and this trend is deterministic in long term. The matrix of inputs for the year ( $k = 1$ ), ( $j$ ) months and ( $i$ ) hours is as Eq. (1).

$$I_{i \times j \times 1} = \begin{bmatrix} I_{1 \times 1} & I_{1 \times 2} & \dots & I_{1 \times 12} \\ I_{2 \times 1} & I_{2 \times 2} & \dots & I_{2 \times 12} \\ \vdots & \vdots & \ddots & \vdots \\ I_{24 \times 1} & I_{24 \times 2} & \dots & I_{24 \times 12} \end{bmatrix} \quad i = 1, 2, \dots, 24; \quad j = 1, 2, \dots, 12; \quad k = 1 \quad (1)$$

The model outputs are optimum operating conditions and maintenance intervals which are derived from the optimization procedure.

$$O_{i \times j \times 1} = \begin{bmatrix} O_{1 \times 1} & O_{1 \times 2} & \dots & O_{1 \times 12} \\ O_{2 \times 1} & O_{2 \times 2} & \dots & O_{2 \times 12} \\ \vdots & \vdots & \ddots & \vdots \\ O_{24 \times 1} & O_{24 \times 2} & \dots & O_{24 \times 12} \end{bmatrix} \quad i = 1, 2, \dots, 24; \quad j = 1, 2, \dots, 12; \quad k = 1 \quad (2)$$

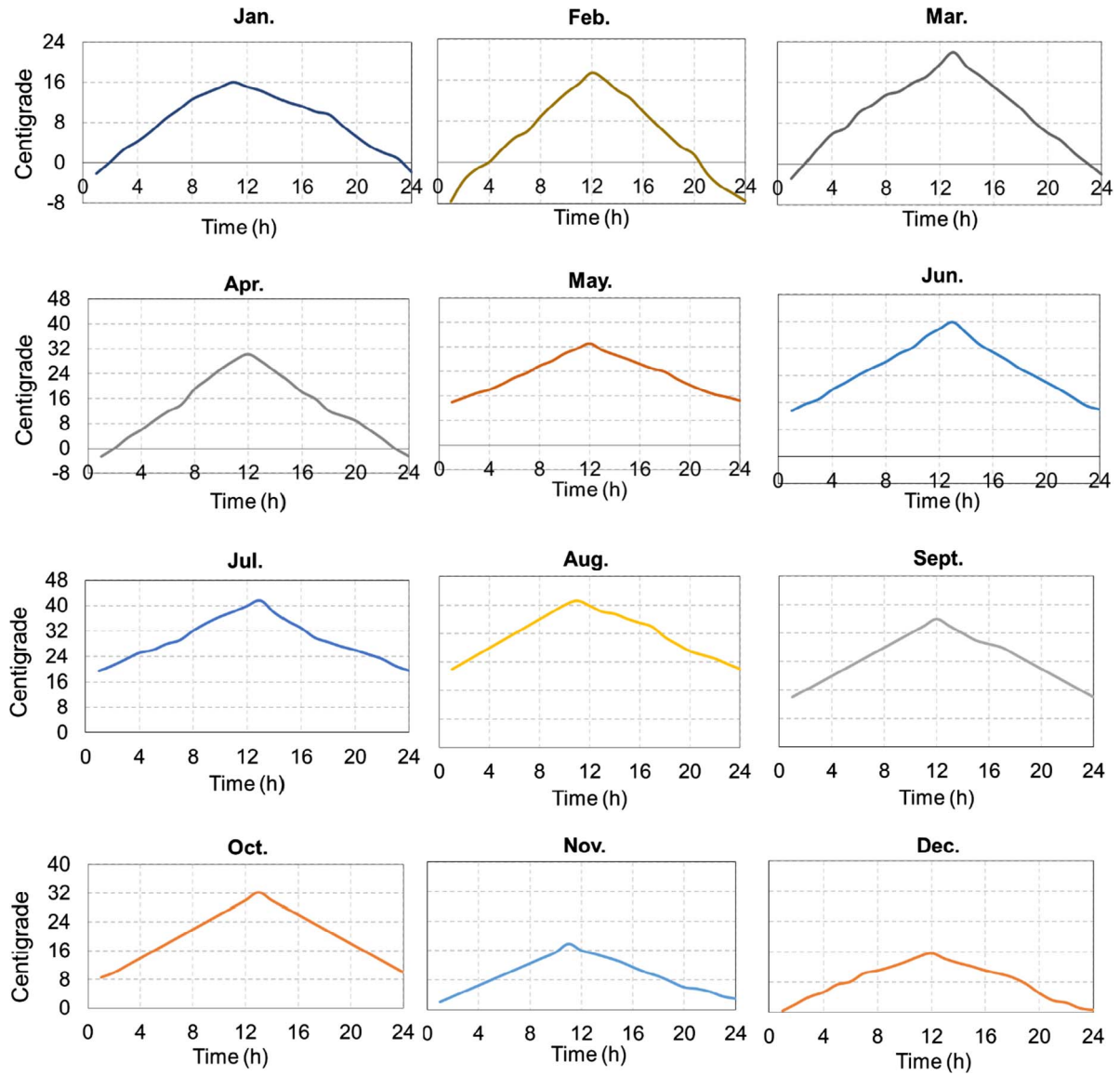


Fig. 8. Variations of ambient temperature.

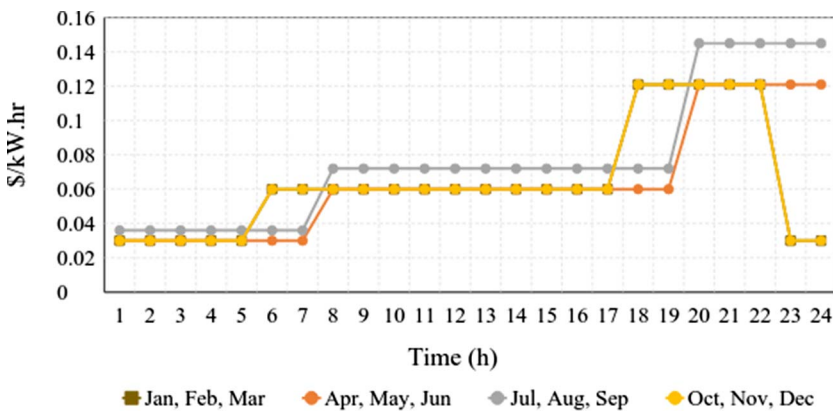


Fig. 9. Variations of electricity price.

### 3.3. Objective function

The objective function maximizes the plant profit over the total operation life time horizon. The profit terms are system incomes (R), and system costs (C). The profit for (k) years, (j) months, (i) hours, and (m) maintenance types can be calculated as Eq. (3).

$$\text{Max } Z = \sum_{m=1}^m \sum_{k=1}^k \sum_{j=1}^{12} \sum_{i=1}^{24} (R_{ijk} - C_{ijkm}) \quad (3)$$

System incomes include selling output power (p) and useful heat (h).

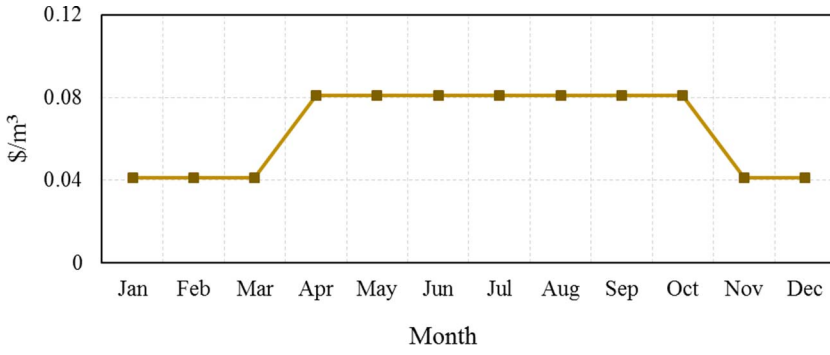


Fig. 10. Variation of fuel cost.

Table 2

Gas turbine (GE 9F.05) maintenance intervals and costs.

No.	Type of inspection	Interval [25]	ERP [32]	Levelized aging cost ( $C^a$ )
	–	EOH	%	\$/EOH
1	Combustion	12,000	2.1	95.8
2	Hot Gas Path	24,000	3.9	88.98
3	Rotor	144,000	31.6	120.16

$$R = \sum_{k=1}^k \sum_{j=1}^{12} \sum_{i=1}^{24} p_{ijk} \times C_{ijk}^p + h_{ijk} \times C_{jk}^h \quad (4)$$

( $C^p$ ) and ( $C^h$ ) are the electricity and heat unit prices, respectively, which change on hourly, monthly and yearly time scales. The system costs are the cost of fuel consumption and components aging cost.

$$C = \sum_{k=1}^k \sum_{j=1}^{12} \sum_{i=1}^{24} \left( h_{ijk} \times C_{ijk}^f + \sum_{m=1}^m EOH_{ijkm} \times C_m^a \right) \quad (5)$$

In Eq. (5), the first term is fuel cost and is calculated based on plant heat rate ( $hr$ ) and unit fuel cost ( $C^f$ ). The second term is aging cost and is defined as hourly preventive and corrective maintenance costs. ( $C^a$ ) is the cost according to the plant maintenance type ( $m$ ) per its EOH. For instance, the ( $C^a$ ) of a gas turbine that has a rotor inspection cost of 17,300,000 \$ after 144,000 EOHs, would be 120.16 \$/EOH.

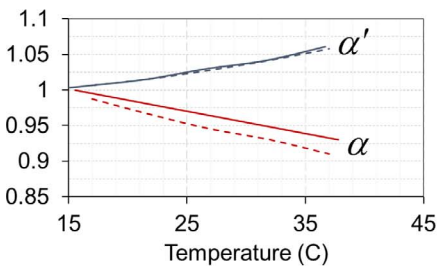
The EOHs, or equivalent operating hours, quantify the stresses that the system experiences as a result of generating energy and will increase according to variables including operating conditions, startups and peak operating hours and is calculated from Eq. (6), [22].

$$EOH = mf \times t \quad (6)$$

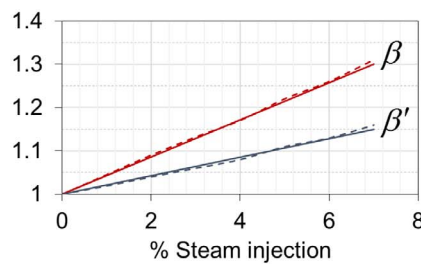
( $t$ ) is hours of system operation and ( $mf$ ) is maintenance factor. Assuming a day sample for each month, the EOH would be as Eq. (7).

$$EOH = \sum_{k=1}^k \sum_{j=1}^{12} \sum_{i=1}^{24} mf_{ijk} \times d_j \quad (7)$$

( $d_j$ ) is the number of days in month ( $j$ ).



— Power — HR - - - Power ref - - - HR ref  
(a)



— Power — HR - - - Power ref - - - HR ref  
(b)

Fig. 11. Validation of model results (solid lines) against experimental results (dotted lines) for ambient temperature and steam injection effects on gas turbine output power and heat rate.

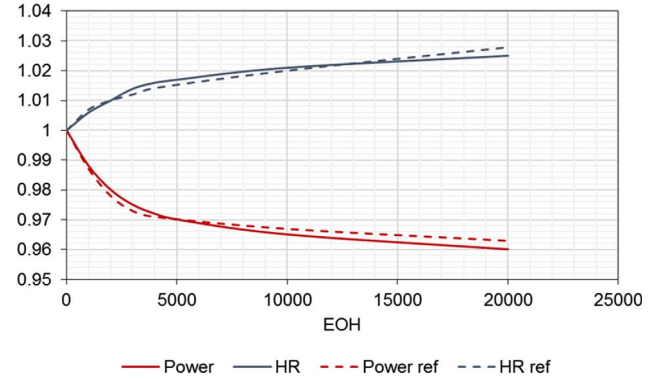


Fig. 12. Validation of model results (solid lines) against experimental results (dotted lines) for aging effects on gas turbine output power and heat rate.

### 3.4. Constraints

The feasible region of the optimization problem is defined by different constraints. Inequality constraints arise from limitations of system operations, and characteristics. An equality constraints are given by the equations which describe components performance functions and components aging.

#### 3.4.1. Operations and characteristics constraints

Each system has an operating limit to be maintained. For instance, the constraint of an operating condition ( $op_{ijk}$ ) with a lower ( $op_{ijk}^l$ ) and upper ( $op_{ijk}^u$ ) bands would be as Eq. (8).

$$op_{ijk}^l \leq op_{ijk} \leq op_{ijk}^u \quad (8)$$

In addition, the preventive maintenance constraint should be applied to the scheduling optimization problem. This constraint represents that the equivalent operating hours of the system must be lower than the system failure EOH which is presented in the standard maintenance policies. The maintenance constraint for the ( $k$ ) years, ( $j$ ) months, and ( $i$ ) hours operation is as Eq. (9), [25].



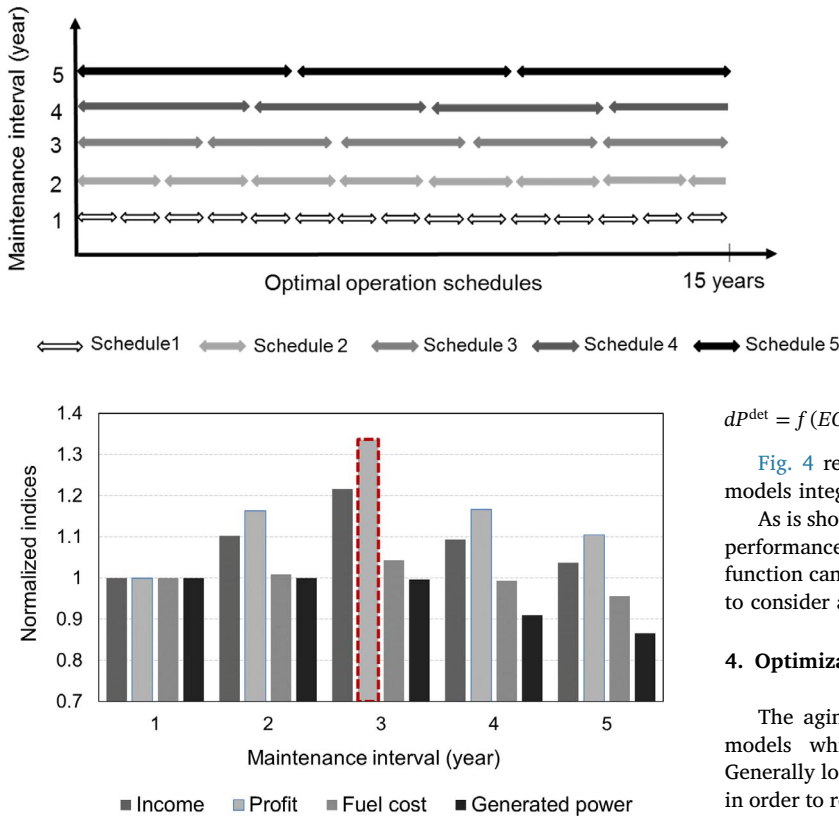


Fig. 13. Optimal operation schedules for different maintenance intervals.

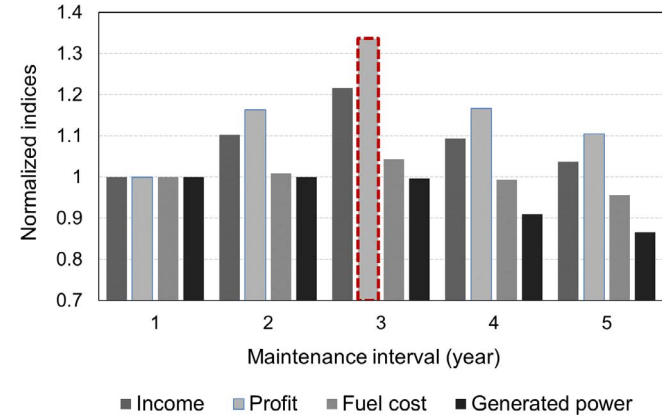


Fig. 14. Normalized indices (income, profit, fuel cost and generated power) as a function of maintenance intervals.

$$\sum_{k=1}^k \sum_{j=1}^{12} \sum_{i=1}^{24} m f_{ij}^k \times d_j \leq EOH^f \quad (9)$$

In the equation, ( $d_j$ ) is the day number of the month ( $j$ ).

### 3.4.2. Components I/O model

The off-design behavior of each component is expressed by means of equations that relate its performance (outputs variables such as power generation and efficiency) to its operating conditions (inputs variables such as fuel and ambient conditions). An I/O model flow data is illustrated in Fig. 3.

The I/O model of a system is constituted by Eq. (10).

$$P = f(A, F, S) \quad (10)$$

System performance ( $P$ ) is a function of ambient conditions ( $A$ ), fuel consumption ( $F$ ) and system operation schedule ( $S$ ). System performance can be the output power ( $p$ ), efficiency ( $\eta$ ), heat rate ( $hr$ ), or maintenance factor ( $mf$ ).

$$P = [p, \eta, hr, mf] \quad (11)$$

Because of the inputs variation, system I/O model outputs vary on hourly, monthly and yearly basis as well.

### 3.4.3. Components aging model

In order to quantify component aging based on the system operation history, EOH approach is introduced. EOH is increased according to system operating conditions. In baseline condition the EOH of one-hour operation would be equal to one. For other operating conditions, EOH will be calculated based on the maintenance factor as Eq. (7). Plant performance deterioration ( $dP^{det}$ ) is a function of EOH [23]. This function reflects the adjusted level of plant performance considering aging effects.

$$dP^{det} = f(EOH) \quad (12)$$

Fig. 4 represents the data flow of the components I/O and aging models integration.

As is shown in Fig. 4, the aging based model represents deteriorated performance over time as a function of operating conditions. This function can be used in the scheduling optimization procedure in order to consider aging effects on optimal solution.

## 4. Optimization algorithm

The aging based optimal scheduling models are usually complex models which require a high structured solution methodology. Generally long term dynamic optimization methodologies are preferred in order to reach a deeper understanding of the process of aging in long term and determining optimum schedule [26]. In this study, a mixed integer nonlinear programming (MINLP) model which includes both continuous and binary variables is employed to estimate plant optimal schedule. The solution method is based on a hybrid heuristic optimization algorithm of BARON and gradient search method. The branch and reduce optimization navigator (BARON) global optimization strategy is used to optimize plant continuous operation schedule. This methodology integrates conventional branch and bound with a wide variety of range reduction tests which most of them are based on duality [27]. The branching algorithm of BARON method is presented in Fig. 5. A random set of partition elements (open nodes) are generated. One of the open nodes is selected and its related relaxation is solved. If the lower bound shows that the node is inferior than the current best known solution, the node is deleted and another node is chosen. If the node cannot be abounded immediately, it is divided into a set of new nodes that replace it on the list of open nodes; this process is branching. The procedure of node selection, bounding and branching is repeated until all the open nodes are abounded.

At this step, the feasible region is branched into several smaller feasible spaces in which the model will be solved. The reduced feasible spaces help to improve the algorithm solution time and accuracy. The model is then solved for all feasible spaces and the global optimal solution will be derived.

The output of the BARON optimization algorithm is long term operation schedule as is shown in Fig. 6. The next step of optimization algorithm is based on search method. In this stage, based on the system maintenance interval and maintenance cost, the best outage plan is derived to maximize lifetime profit of the system. Then results are checked if they meet the stopping criteria. Finally, the optimum decision variable elements including plant operating conditions and outage plan will be derived.

## 5. Case study

### 5.1. Plant description

The proposed framework is employed to determine the optimal

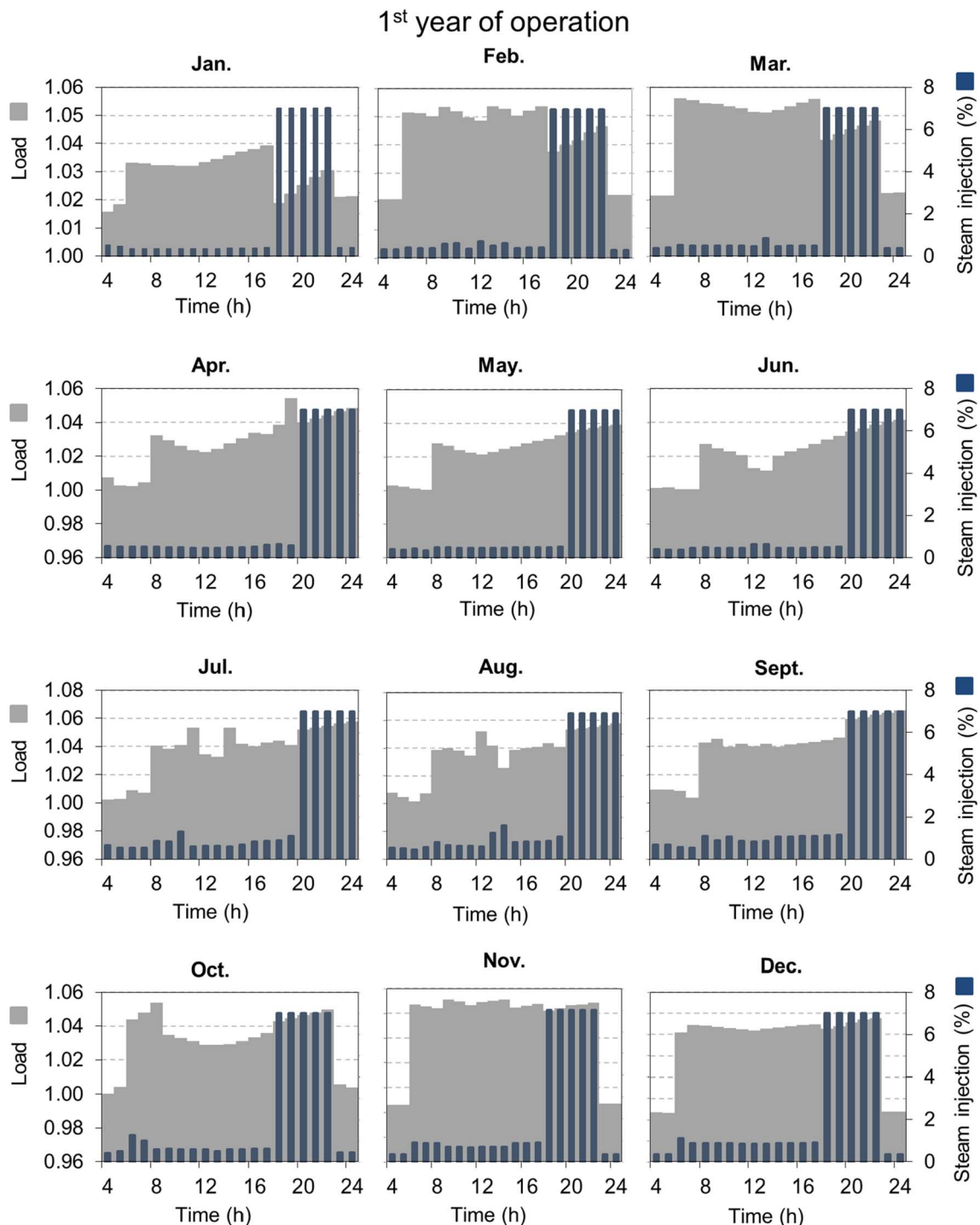


Fig. 15. Optimal hourly schedule for a typical day of each month of the first year of operation.

schedule of a gas turbine power plant that serves a stationary load. The optimal schedule includes optimal operating conditions (hourly load and steam injection) and maintenance intervals during 15 years of operation.

The studied gas turbine is a 9F.05 model of GE products. The flow diagram of the system is presented in Fig. 7.

In addition, the main characteristics of the studied gas turbine are presented in Table 1 and more details of the system are provided in Ref. [28].

## 5.2. Input profiles

The hourly variations of the ambient temperature for 12 types of days are gathered from Tehran/Mehrabad weather station and are shown in Fig. 8, [29]. As it is expected, the ambient temperature is relatively low in the early morning, keeps increasing until noon, then decreases and reaches its minimum at midnight. The monthly variations show that the average ambient temperature is relatively low in January, keeps increasing till August, and then decreases and reaches its minimum again in January.

Fig. 9 presents the variations of the electricity price [30]. As can be seen, the price of electricity is higher at peak-loads than off-loads hours.

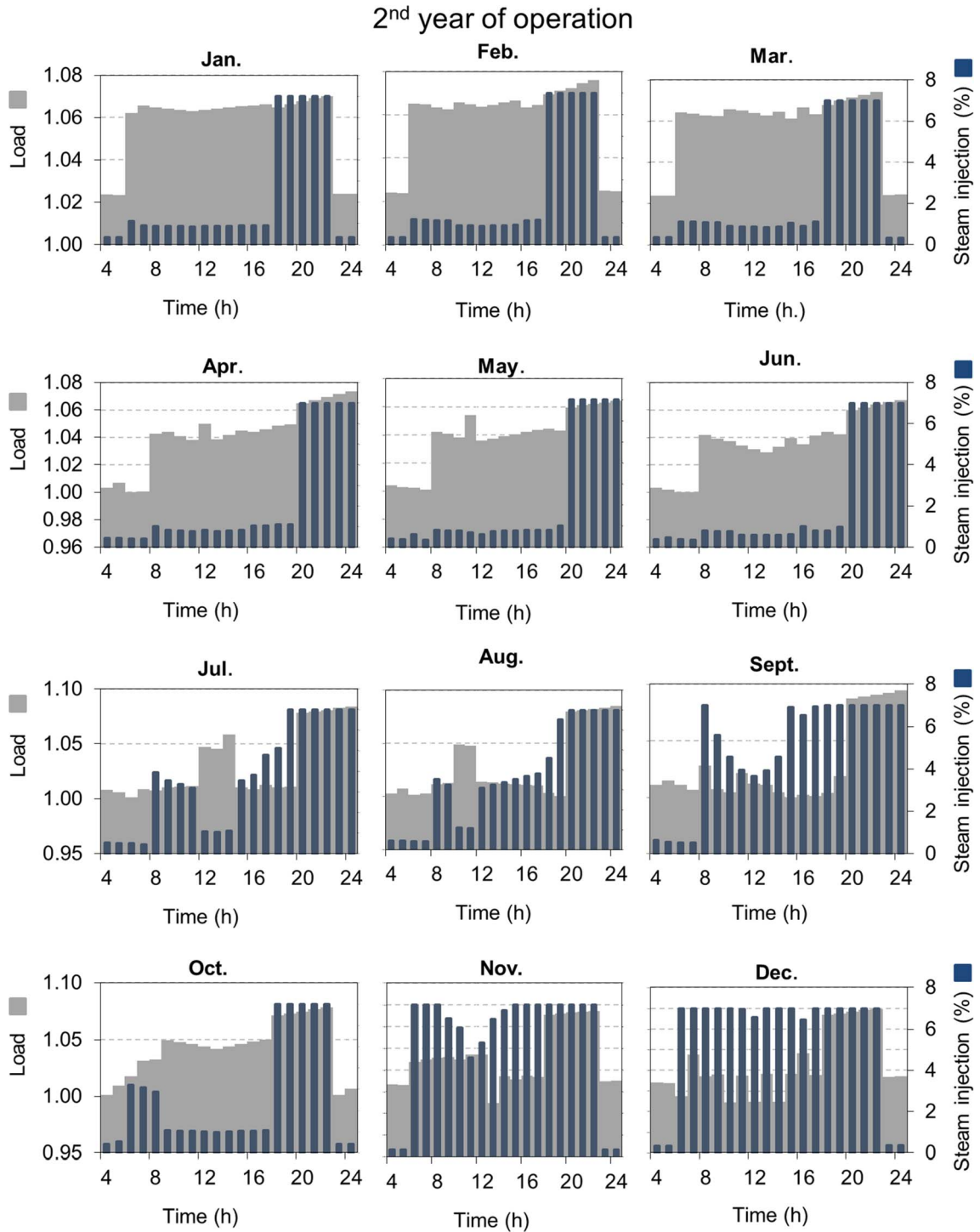


Fig. 16. Optimal hourly schedule for a typical day of each month of the second year of operation.

The monthly variation of fuel cost is presented in Fig. 10, [31]. The figure shows that in cold months, natural gas price is lower than warm months which is due to higher fuel demand for heating in cold months.

### 5.3. Scheduling formulation

The aging based optimal scheduling for profit maximization, relies on the knowledge about economic performance of power plants. A projection of the effect of operating conditions and maintenance intervals on power plant output and performance deterioration are necessary to evaluate power plant costs and incomes and consequently

power plant profit [15]. The objective of the optimization as presented in Eq. (13) is to maximize the long term profitability ( $Z$ ) of a gas turbine power plant. The decision variables are operating conditions and maintenance intervals which are varying on hourly ( $i = 1, 2, 3, \dots, 24$ ), monthly ( $j = 1, 2, 3, \dots, 12$ ) and yearly ( $k = 1, 2, 3, \dots, 15$ ) basis.

$$\text{Max } Z = \sum_{k=1}^{15} \sum_{j=1}^{12} \sum_{i=1}^{24} (R_{ijk} - C_{ijk}) \quad (13)$$

Gas turbine plant income ( $R_{ijk}$ ) is the income of selling electricity to the grid.

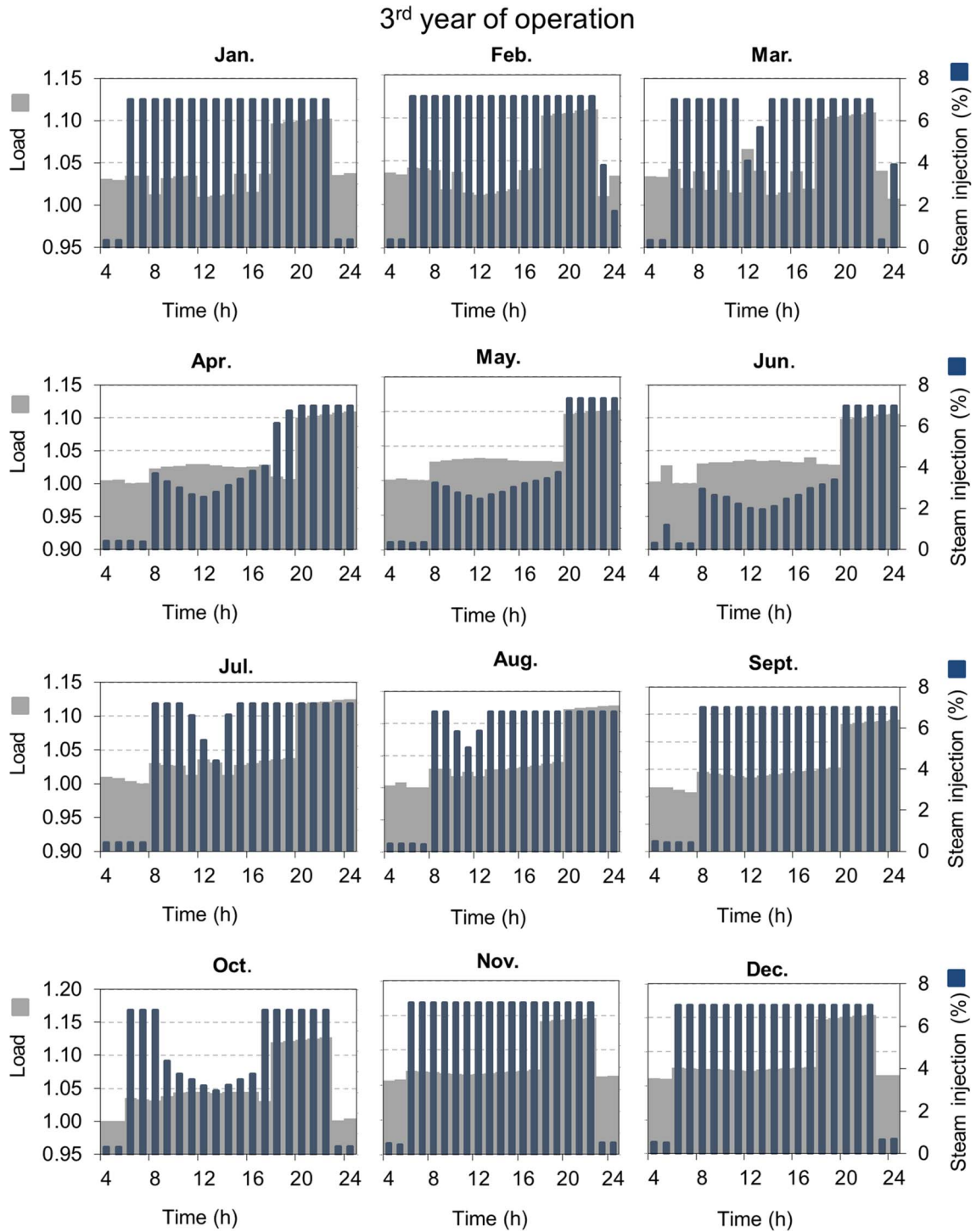


Fig. 17. Optimal hourly schedule for a typical day of each month of the third year of operation.

$$R_{ijk} = p_{ijk} \times C_{ijk}^p \quad (14)$$

$(p_{ijk})$  is the output power and  $(C_{ijk}^p)$  is the hourly unit price of electricity. Moreover, plant costs  $(C_{ijk})$  are the cost of fuel consumption and aging cost (maintenance hourly cost).

$$C_{ijk} = hr_{ijk} \times C_{ijk}^f + \sum_{m=1}^3 mf_{ijkm} \times d_j \times C_m^a \quad (15)$$

$(hr_{ijk})$  is the gas turbine heat rate and  $(C_{ijk}^f)$  is the monthly unit cost of natural gas.  $(mf_{ijkm})$  is the maintenance factor of inspection type (m).  $(C^a)$  is the levelized cost of aging according to the inspection type (m).

Table 2. presents the inspection cost as a percentage of equipment replacement price (ERP) for three types of inspection [25,32].

As can be seen, all terms of the profit are affected by components aging. Generated power and heat rate deteriorates over time due to components aging. Moreover, the aging cost reflects hourly cost of components aging.

To show the effect of the operating conditions on profit terms different coefficient factors are defined. The plant output power deviates from the base load output power ( $P^0$ ) of gas turbine because of the change in ambient temperature, steam injection, operating load and components aging as Eq. (16), [33].

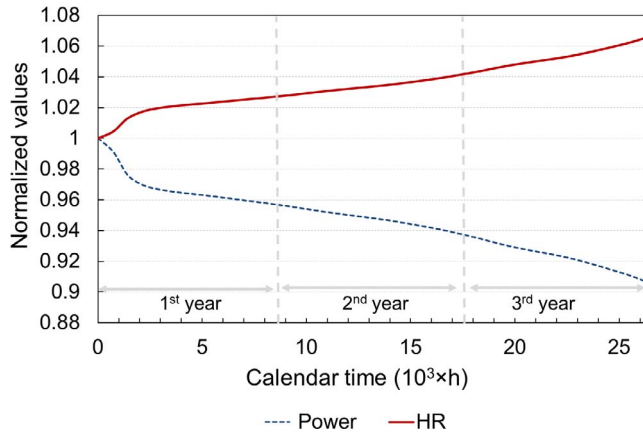


Fig. 18. Gas turbine performance (output power and heat rate) deterioration through calendar time.

$$p_{ij} = P^0 \times \alpha \times \beta \times \lambda \times \delta \quad (16)$$

In this equation,  $(\alpha)$ ,  $(\beta)$ ,  $(\delta)$ , and  $(\lambda)$  represent the correction factors of temperature, steam injection, system load percentage and aging, respectively. These correction factors can be calculated as Eqs. (17)–(19), [34–36].

$$\alpha = -0.007 \times T + 1.1076 \quad (17)$$

$$\beta = (1 + 0.042857 \times \% \dot{m}_s) \quad (18)$$

$$\lambda = 0.03 \exp(-4.9 \times 10^{-4} \times EOH) + 0.97 \exp(-5 \times 10^{-7} \times EOH) \quad (19)$$

$(T)$ ,  $(\dot{m}_s)$ , and  $(EOH)$  are the ambient temperature, steam injection percentage, and equivalent operating hour. These functions are derived from system historical data [34–36].

In addition, plant heat rate deviates from its standard value  $(HR^0)$  and can be calculated for different operating conditions based on the Eq. (20), [33].

$$hr_{ij} = HR^0 \times \alpha' \times \beta' \times \lambda' \times \delta' \quad (20)$$

The  $(\alpha')$ ,  $(\beta')$ ,  $(\delta')$ , and  $(\lambda')$  represent the correction factors of temperature, steam injection, system load percentage, and aging, respectively. The correction factors are formulated as Eqs. (21)–(24), [34–36].

$$\alpha' = 3 \times 10^{-5} \times T^2 + 1.2 \times 10^{-3} \times T + 0.9789 \quad (21)$$

$$\beta' = (1 - 0.021429 \times \% \dot{m}_s) \quad (22)$$

$$\delta' = -0.0002\delta^5 + 0.0036\delta^4 - 0.0322\delta^3 + 0.136\delta^2 - 0.3023\delta + 1.365 \quad (23)$$

$$\lambda' = 1.02 \exp(3.4 \times 10^{-7} \times EOH) - 0.02 \exp(-3.9 \times 10^{-4} \times EOH) \quad (24)$$

Eqs. (21)–(24) are resulting from historical data of a gas turbine power plant [34–36]. In addition, GE company has developed maintenance factor functions for heavy duty gas turbines. The functions determine maintenance factors based on system load and steam

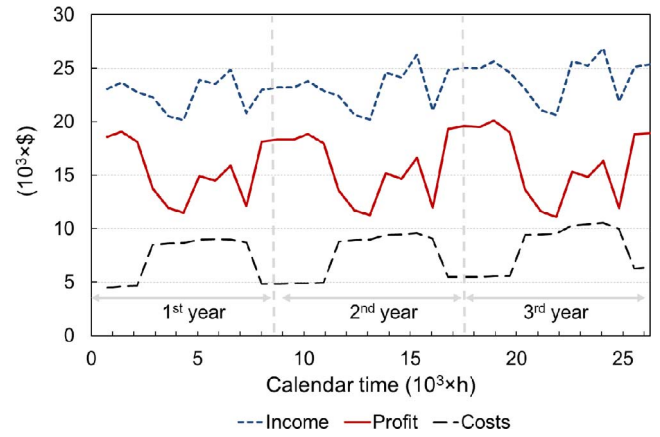


Fig. 20. System hourly cash flow over calendar lifetime.

Table 3

Comparison between two optimal operating schedules.

	Aging based schedule	Base case schedule	Increase/decrease percentage (%)
Profit (M\$/yr.)	109.17	105.1	4
Costs (M\$/yr.)	55.14	55.88	-1
Income (M \$/yr.)	164.31	160.96	2

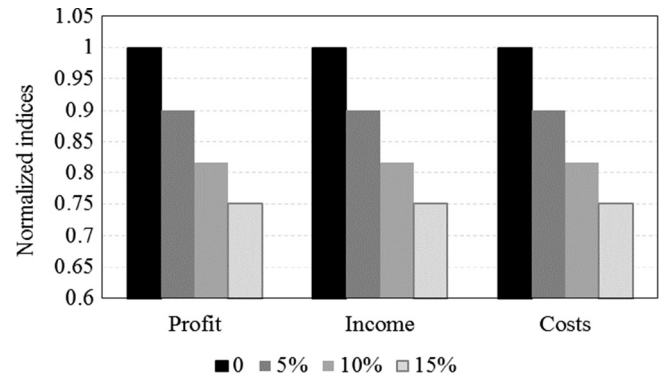


Fig. 21. System profit, income and costs for different interest rates.

injection. The maintenance factors for combustion, hot gas path, and rotor inspections are calculated as Eqs. (25)–(30), [25].

$$mf^1(\text{combustion inspection}) = k^1 \times s \quad (25)$$

$$k^1 = \text{Max}(1, \exp(0.34(\% \dot{m}_s - \%1))) \quad (26)$$

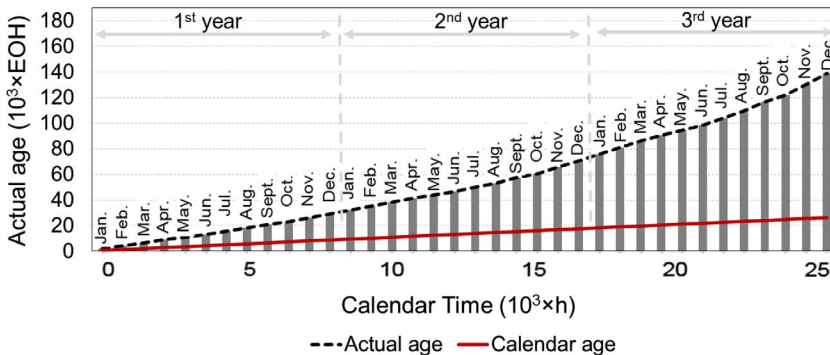


Fig. 19. Actual and calendar age of the studied gas turbine.



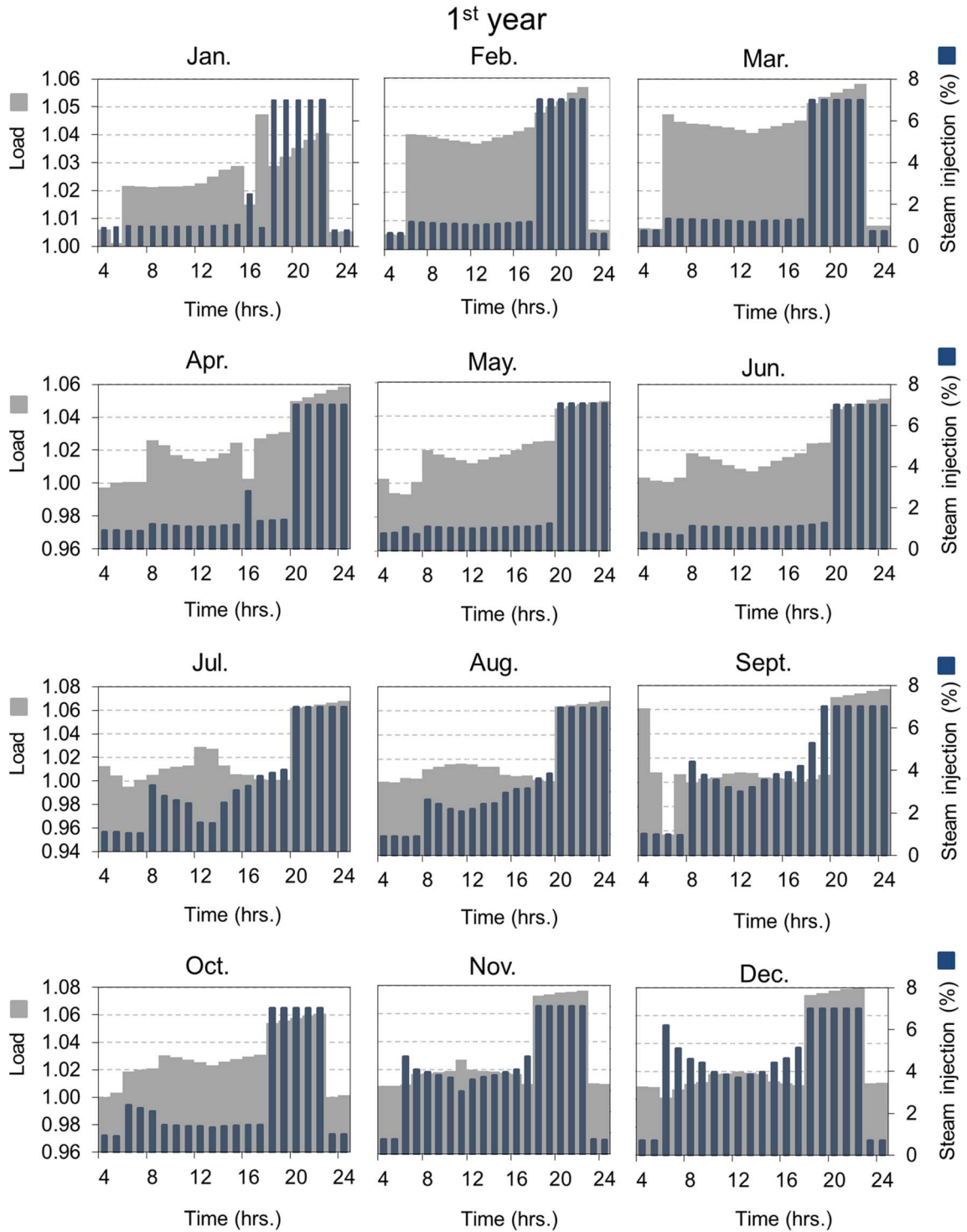


Fig. 22. Optimal hourly schedule for a typical day of each month of the first year of operation under 15% interest rate.

$$s = \begin{cases} 1 & \text{up to base load} \\ \exp(0.023 \times (10.25 \times \% \delta - 1025)) & \end{cases} \quad (27)$$

$$mf^2(\text{hot gas path inspection}) = k^2 \times s \quad (28)$$

$$k^2 = 1 + (0.55 \times \% \dot{m}_s) \quad (29)$$

$$mf^3(\text{rotor inspection interval}) = \begin{cases} 2, & \text{peak} \\ 1, & \text{non-peak} \end{cases} \quad (30)$$

operating conditions including load ( $\delta$ ) and steam injection ( $\dot{m}_s$ ). The maintenance factor reflects the effect of operating conditions on system actual age (EOH) as Eq. (6).

In addition, the case study model has several constraints. For instance, it is assumed that the gas turbine plant would operate until reaches its inspection intervals as presented in Table 2, [25].

$$\sum_{k=1}^{15} \sum_{j=1}^{12} \sum_{i=1}^{24} mf_{ijk}^m \times d_i \leq EOH^m \quad m = 1, 2, 3 \quad (31)$$

As shown, each maintenance factor depends on gas turbine

Moreover, it is assumed that gas turbine startup takes 2 h and will

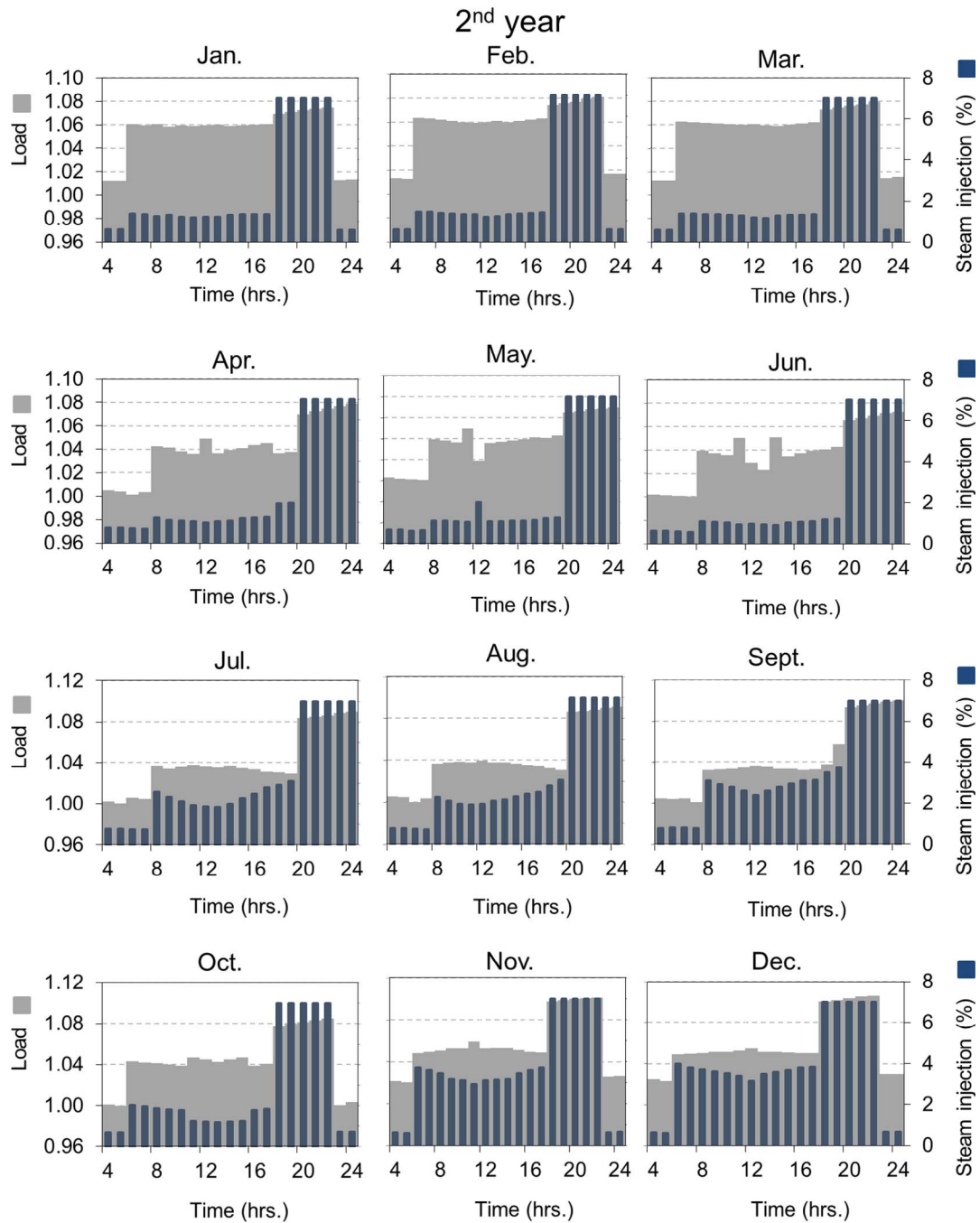


Fig. 23. Optimal hourly schedule for a typical day of each month of the second year of operation under 15% interest rate.

consume more fuel until system reaches nominal operating status.

$$\delta_{i-1} \times \delta_{i+1} \times \varepsilon \leq \delta_i \quad (32)$$

where  $\varepsilon$  is a small positive infinitesimal quantity. This constraint shows that system cannot be offline just for one hour and the minimum offline hours in a row is two (startup time).

## 6. Results and discussion

The solution procedure is carried out based on a hybrid heuristic optimization algorithm. The general algebraic modelling system (GAMS) software is used to obtain the optimal values that maximizes gas turbine plant lifetime profit. The GAMS is a major software modelling facility that houses various software solver tools such as BARON [27].

In this section, results of the gas turbine model are presented and the effect of temperature, steam injection and EOH on system output power and heat rate generation is analyzed. Then, the studied gas turbine schedule (maintenance intervals and operating conditions including load and steam injection) is optimized for 15 years of system operation using proposed framework. Finally, performance deterioration and economic evaluation of the studied gas turbine operating at the optimal schedule are presented.

### 6.1. Validation

In this section, the I/O and aging models of the gas turbine are validated. The output power and heat rate are considered as two criteria of gas turbine performance. Fig. 11(a) shows the correction factors of gas turbine output power ( $\alpha$ ) and heat rate ( $\alpha'$ ) as a function of

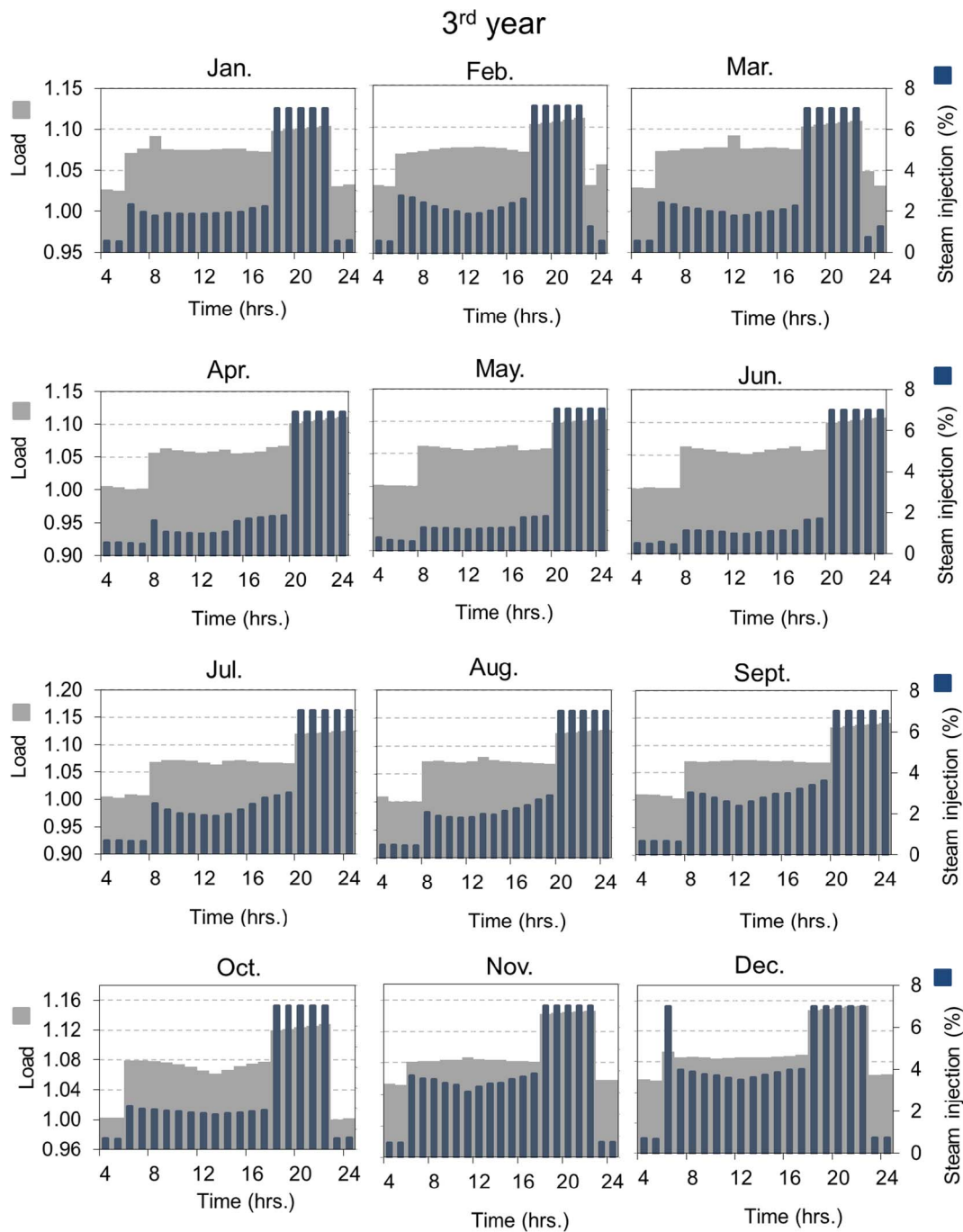


Fig. 24. Optimal hourly schedule for a typical day of each month of the third year of operation under 15% interest rate.

ambient temperature. As ambient temperature increases, the compressor work increases and as a result output power decreases and heat rate grows. The model outputs are validated using experimental data gathered by [34]. As is shown in the figure, the model outputs provide a reasonable fit to the experimental data.

Steam injection is a technique for gas turbine power augmentation. The effect of steam injection on output power and heat rate correction factors ( $\beta, \beta'$ ) is illustrated in Fig. 11(b). As it is presented, seven percent steam injection can increase heat rate and output power by around 15 and 30 percent, respectively. In the figure the comparison between model output and experimental results published by [35] are performed. Based on the results, the biggest difference observed is under 3% that is negligible in our study.

Performance deterioration as a function of EOH is used to validate

aging effects on performance deterioration over time. Fig. 12 presents the output power and heat rate correction factors ( $\lambda, \lambda'$ ) through system equivalent operating hours. As can be seen, the gas turbine output power drops and heat rate increases more quickly at low EOHs, as the gas turbine performance is very dependent on component aging and the degradation rate is higher at the beginning of system operating hours. In addition, as it can be seen, the model prediction is in good agreement with the experimental data published by [36]. At higher EOHs, model indicates lower output power and heat rate deterioration in comparison with experimental data. However, the modeling results are nearly close to the experimental data in this range as well.

## 6.2. Optimal maintenance scheduling results

The optimum operating schedule depends on the continuous operation time span and maintenance interval. Fig. 13 indicates that optimum operating conditions is changed due to different maintenance intervals. However, it is repeated for a specific maintenance interval during 15 years of operation.

In order to find the optimum maintenance and operation schedule, the model is solved for 1–5 years of maintenance intervals and optimum operating schedule and plant indices including annual income, annual profit, annual fuel cost, and annual generated power are derived. The normalized expected indices as a function of maintenance intervals are illustrated in Fig. 14. It is found that as the maintenance inspection is postponed, the profit increases, until it reaches a maximum level. Afterward, the profit keeps decreasing if the maintenance inspections are postponed further. The results show that maximum profit is achieved when the maintenance is performed in the 3<sup>rd</sup> year of system operation.

## 6.3. Optimal operation scheduling results

In this section, the optimized operation schedule for the derived optimum maintenance interval is presented. Figs. 15–17 show the optimum hourly gas turbine load and steam injection for three years of operation. As can be seen, daily load and steam injection follow almost the same trend seasonally. As Figs. 9 and 10 show, the electricity price and natural gas cost profiles are the same for fall and winter. As a result, the optimum operation profiles in these seasons are almost the same as well. As it is shown, load is higher in the middle hours of the day. It increases as it goes from beginning hours into night and decreases in the last hours of the day. Steam injection is low at the first hours of the day and increases during peak hours and decreases in the last two hours. In spring and summer, the load and steam injection are low at the first hours of the day and increases gradually till midnight. This trend is due to the dynamics of electricity price and fuel cost in these seasons.

As indicated by annual comparison, the power plant is scheduled to operate in a relative low output level with low power augmentation during the first months of operation. However, as shown, the gas turbine is turned on to the highest output level with steam injection at highest level during the last months of operation.

## 6.4. Performance deterioration evaluations

Performance deterioration through time is an important issue in evaluating gas turbine power plants operation. All power plants experience losses in performance over time, even under normal operating conditions. However, performance losses can be optimized to have a lower economic impact. In the proposed framework, the performance deterioration is optimized in a most economical way. In this section performance deterioration for the derived optimal schedule (operation and maintenance) is presented. Fig. 18 depicts the output power and heat rate deterioration during system operating lifetime. As shown in Fig. 18, the performance deteriorates rapidly at the beginning hours of operation due to higher degradation rate in the first hours of operation [37]. Afterward the deterioration rate increases gradually that is because of the smooth degradation rate and maintenance factor growth. Results indicate that after three years of operation, output power and heat rate deteriorate at about 10 and 7 percent, respectively.

The relationship between gas turbine aging and calendar time is investigated in Fig. 19. The age of a gas turbine depends on factors including the chronological age, ambient conditions, number of startup, load, and steam injection. Determining the age of a gas turbine is further complicated by the fact that individual components age differently depending on these factors. However, the average age of a gas turbine can be evaluated based on the maintenance factor and is equal to the accumulative equivalent operating hours of the system as presented in

Eq. (7). As can be seen in Fig. 19, the gas turbine age growth up to 140,000 EOHs through three years of operation. The actual and calendar age difference increases as time passes. For instance, the actual age is around 3, 4, and 5 times higher than calendar age after one, two and three years of operation, respectively. In fact, the ratio of the actual age to the calendar age at time (t) shows the average hourly maintenance factor of the gas turbine operating until time (t).

## 6.5. Economic evaluations

Fig. 20 depicts the cash flow of the gas turbine power plant. In order to analyze system profit, the income of system and costs are concurrently illustrated in Fig. 20. Profiles fluctuation is because of the seasonal variations of the market signals and optimal operation schedule. According to the results, the average income is low in the beginning and end periods of each year, due to the lower electricity price. At lower electricity price, system prefers to generate power at lower rate to reduce components aging and fuel costs. However, from the beginning of July to the end of September, the electricity price is higher and the income of generating power outweigh aging and fuel cost. During period April to Jun, the income is in its lowest levels if compared with other months because of reducing energy market price. Furthermore, it is found that the scheduled system cost follows the same trend as that of fuel cost in a year. It increases as it goes from winter into summer and decreases from fall to spring. Furthermore, the fuel cost profile is repeated annually and its average value increases over time as a result of components aging and heat rate deterioration.

## 6.6. Aging consideration effectiveness

The optimized aging based schedule is compared with the base case schedule (full load without steam injection) in terms of economical comparison that is summarized in Table 3. In fact, base case schedule is the output of a scheduling optimization model without considering aging effects. Results indicate that the aging based optimal schedule leads to a more efficient and economic operation of gas turbine than the base case schedule. Based on the results, during 15 years of operation, the operation costs are nearly the same. However, operating at aging based optimal schedule increases gas turbine annual profit up to 4% that shows the effectiveness of proposed framework.

## 6.7. Sensitivity analysis on interest rate

Since the problem of optimal scheduling is a long term optimization problem, it is more realistic to take the uncertainties of investment opportunities into consideration. In this study, three different interest rates are considered in the optimization model.

The optimal operating and maintenance schedule is derived for three different interest rates of 5, 10 and 15%. Fig. 21 shows the normalized income, cost, and profit of the plant under different levels of interest rates. As can be seen, the net present values of profit, income, and costs decreases by increasing the interest rate.

Figs. 22–24 show the optimum hourly load and steam injection for three years of operation under 15% interest rate. It should be noted that, the model is solved for 1–5 years of maintenance intervals and optimum operating schedules are derived. The results show that maximum profit is achieved when the maintenance is performed in the 3<sup>rd</sup> year of system operation.

Results show that considering interest rate changes optimal schedule entirely. Increasing interest rate leads to an operation schedule with higher steam injection and lower load at the beginning hours of operation. The increase in steam injection level and load are the ways of power augmentation. Steam injection can increase power with lower fuel consumption in comparison with load increment. However, has a higher degradation rate and deteriorates system performance more rapidly.



In the case of ignoring interest rate, system operates at the operation schedule with lower degradation rate over time. For instance, the power is increased at the first months of operation. Conversely, the power augmentation is handled by steam injection at the end of the life.

On the other hand, under high interest rates, system prefers to operate at higher income and lower fuel cost at the beginning hours of operation despite the increase in performance deterioration over time. It is because of the lower value of cash flow over time under high interest rate environment.

## 7. Conclusions

In this paper an aging based optimal scheduling framework is proposed to maximize power plants lifetime profit. The framework considers components aging effects in the optimization procedure. The equivalent operating hour approach is introduced to determine the effect of component aging on system performance deterioration, aging cost and consequently optimal schedule. The aging cost is the hourly maintenance cost that is considered as a term in the objective function. This shows the dependency of maintenance cost on operation schedule using maintenance factor coefficient.

The framework is developed based on the mixed integer nonlinear dynamic optimization approach. A two stage optimization algorithm is used as the solution methodology. The first stage is based on the BARON method and determines the continuous optimum operating schedule and the second stage is a search method that provides the optimal maintenance schedule.

Finally, the proposed methodology was applied to a gas turbine to evaluate the framework effectiveness. Results show that the EOH approach is a promising method to predict gas turbine performance as it degrades over time. Moreover, the obtained results from scheduling optimization model show that the aging based scheduling framework can be an appropriate approach to achieve maximum lifetime profit. Through the presented analysis, it is shown that operation scheduling and maintenance intervals should be optimized simultaneously. Furthermore, when compared to the base case schedule (optimal schedule without considering aging effects), the aging based framework is able to achieve higher profit up to 4% annually.

Furthermore, a sensitivity analysis on interest rate is performed. It is shown that optimal schedule depends on interest rate level strongly and in schedule optimization problems economic knowledge and assumptions are essential.

In this study, the framework objective function is power plant lifetime profit. However, any other objective function, such as primary energy consumption, plant efficiency, or pollutant emissions, could be implemented in the framework here defined.

The major concluding remarks can be summarized as follows:

- Results demonstrate gas turbine power and heat rate deteriorate as time pass, and the economic impact of these issues are significant. Therefore, aging based optimal scheduling should be performed to achieve maximum lifetime profit.
- The optimization results show that the optimal operation schedule depends on the maintenance interval. Therefore, operation and maintenance schedule should be optimized simultaneously for the entire lifetime of the plant.
- To show the effectiveness of the developed framework, model outputs are compared with an optimal case that doesn't consider aging effects in the optimization procedure. Results illustrate operating at aging based optimal schedule is more beneficial for long term profit maximization and the power plant will have 4% higher annual profit.

## Funding

This research did not receive any specific grant from funding

agencies in the public, commercial, or not-for-profit sectors.

## References

- [1] Froger A, Gendreau M, Mendoza JE, Pinson É, Rousseau L-M. Maintenance scheduling in the electricity industry: a literature review. *Eur J Oper Res* 2016;251:695–706. <http://dx.doi.org/10.1016/j.ejor.2015.08.045>.
- [2] Alamaniotis M, Grelle A, Tsoukalas LH. Regression to fuzziness method for estimation of remaining useful life in power plant components. *Mech Syst Signal Process* 2014;48:188–98. <http://dx.doi.org/10.1016/j.ymssp.2014.02.014>.
- [3] Roshandel R, Parhizkar T. Degradation based optimization framework for long term applications of energy systems, case study: solid oxide fuel cell stacks. *Energy* 2016;107:172–81. <http://dx.doi.org/10.1016/j.energy.2016.04.007>.
- [4] Sauhats A, Coban HH, Baltutis K, Broka Z, Petrichenko R, Varfolomejeva R. Optimal investment and operational planning of a storage power plant. *Int J Hydrogen Energy* 2016;41:1–11. <http://dx.doi.org/10.1016/j.ijhydene.2016.03.078>.
- [5] Zamani AG, Zakariazadeh A, Jadid S. Day-ahead resource scheduling of a renewable energy based virtual power plant. *Appl Energy* 2016;169:324–40. <http://dx.doi.org/10.1016/j.apenergy.2016.02.011>.
- [6] Nosratabadi SM, Hooshmand RA, Gholipour E. Stochastic profit-based scheduling of industrial virtual power plant using the best demand response strategy. *Appl Energy* 2016;164:590–606. <http://dx.doi.org/10.1016/j.apenergy.2015.12.024>.
- [7] Kitsutaka Y, Tsukagoshi M. Method on the aging evaluation in nuclear power plant concrete structures. *Nucl Eng Des* 2014;269:286–90. <http://dx.doi.org/10.1016/j.nucengdes.2013.08.041>.
- [8] Sivakumar L, Devi S. Implementation of VLSI model as a tool in diagnostics of slowly varying process parameters which affect the performance of steam turbine. *Appl Soft Comput J* 2014;24:730–41. <http://dx.doi.org/10.1016/j.asoc.2014.08.015>.
- [9] Haghighat Mamaghani A, Najafi B, Casalegno A, Rinaldi F. Long-term economic analysis and optimization of an HT-PEM fuel cell based micro combined heat and power plant. *Appl Therm Eng* 2016;99:1201–11. <http://dx.doi.org/10.1016/j.applthermaleng.2016.02.021>.
- [10] Zhao Y, Volovoi V, Waters M, Mavris D. A profit-based approach for gas turbine power plant outage planning. *J Eng Gas Turb Power* 2006;128:806–14. <http://dx.doi.org/10.1115/1.2179466>.
- [11] Zhao Y, Volovoi V, Waters M, Mavris D. A sequential approach for gas turbine power plant preventative maintenance scheduling. *J Eng Gas Turb Power* 2006;128:796–805. <http://dx.doi.org/10.1115/1.2179470>.
- [12] Zhao Y. An integrated framework for gas turbine based power plant operational modeling and optimization. Georgia Institute of Technology; 2005. PhD Thesis.
- [13] Gamarra C, Guerrero JM. Computational optimization techniques applied to microgrids planning: a review. *Renew Sustain Energy Rev* 2015;48:413–24. <http://dx.doi.org/10.1016/j.rser.2015.04.025>.
- [14] Yang Z, Li K, Foley A. Computational scheduling methods for integrating plug-in electric vehicles with power systems: a review. *Renew Sustain Energy Rev* 2015;51:396–416. <http://dx.doi.org/10.1016/j.rser.2015.06.007>.
- [15] Zhao Y, Volovoi VV, Waters M, Mavris DN. Power plant systems operational scheduling using a dual-time scale. 10th AIAA/ISSMO multidisciplinary anal optim conf. New York: AIAA; 2004. p. 3824–37.
- [16] Das Gupta S, Tobin JK, Pavel L. A two-step linear programming model for energy-efficient timetables in metro railway networks. *Transp Res Part B Methodol* 2016;93:57–74. <http://dx.doi.org/10.1016/j.trb.2016.07.003>.
- [17] Nip K, Wang Z, Wang Z. Scheduling under linear constraints. *Eur J Oper Res* 2016;253:290–7. <http://dx.doi.org/10.1016/j.ejor.2016.02.028>.
- [18] Lu Y, Wang S, Sun Y, Yan C. Optimal scheduling of buildings with energy generation and thermal energy storage under dynamic electricity pricing using mixed-integer nonlinear programming. *Appl Energy* 2015;147:49–58. <http://dx.doi.org/10.1016/j.apenergy.2015.02.060>.
- [19] Jin X, Mu Y, Jia H, Wu J, Xu X, Yu X. Optimal day-ahead scheduling of integrated urban energy systems. *Appl Energy* 2016. <http://dx.doi.org/10.1016/j.apenergy.2015.12.090>.
- [20] Bonvin G, Demasse S, Pape C, Maizi N, Mazaauric V, Samperio A. Optimal day-ahead scheduling of integrated urban energy systems. *Appl Energy* 2016;1–13. <http://dx.doi.org/10.1016/j.apenergy.2016.07.071>.
- [21] Heinz P, Bloch CS. *Process plant machinery*. second ed. Butterworth-Heinemann; 1998.
- [22] Radin Y, Kontorovich T. Equivalent operating hours concept for ccpp components reliability evaluation. *Int Conf Power Energy Syst Lect Notes Inf Technol* 2012;13:175–8.
- [23] Leusden CP, Sorgenfrey C, Dümmel L. Performance benefits using siemens advanced compressor cleaning system. *J Eng Gas Turb Power* 2004;126:763–9. <http://dx.doi.org/10.1115/1.1787512>.
- [24] Sun W. New optimization techniques for power system generation scheduling. Iowa State University; 2011. PhD Thesis.
- [25] Janawitz J, Masso J, Childs C. Heavy-duty gas turbine operating and maintenance considerations. GE report. Atlanta 2015. doi:GER-3620M.
- [26] Nie Y. Integration of scheduling and dynamic optimization: computational strategies and industrial applications. Carnegie Mellon university; 2014. PhD Thesis.
- [27] Amosa MK, Majazi T. GAMS supported optimization and predictability study of a multi-objective adsorption process with conflicting regions of optimal operating conditions. *Comput Chem Eng* 2016;94:354–61. <http://dx.doi.org/10.1016/j.compchemeng.2016.08.014>.
- [28] GE 9f.05 Fact Sheet; n.d. < <https://powergen.gepower.com/content/dam/>



- [gepower-pgdp/global/en\\_US/documents/product/gasturbines/Fact Sheet/9F.05-fact-sheet-2016.pdf](http://gepower-pgdp/global/en_US/documents/product/gasturbines/Fact Sheet/9F.05-fact-sheet-2016.pdf) > .
- [29] Iran Meteorological Organization Website; n.d. < <http://irimo.ir/> > .
  - [30] Iran Ministry of Energy Website; n.d. < <http://moe.gov.ir/> > .
  - [31] National Iranian Gas Company Website; n.d. < <http://nigc.ir/> > .
  - [32] Bevc F, Rominger K, Mack R, Tuthil R. Equipment replacement provision of the routine maintenance, repair and replacement exclusion; reconsideration; final rule, 69 Fed. Reg. 40278. Gas Turbine Association Report, Virginia 22066; 2004.
  - [33] Estimating gas turbine performance. GE Power Systems Report; n.d. doi:GTS-111D.
  - [34] Silva E, Assato M, Lima R. Performance prediction of gas turbine under different strategies using low heating value fuel. Turbine Tech Conf Expo, San Antonio, Texas: ASME; 2013, p. 1–8.
  - [35] Xueyou W, Yingxin W, Jiguo Z. PG5361 steam injection cogeneration plant. Int gas turbine aeroengine congr expo, Ohio: ASME; 1993.
  - [36] Boyce MP, Gonzalez F. A study of on-line and off-line turbine washing to optimize the operation of a gas turbine. J Eng Gas Turb Power 2007;129:114. <http://dx.doi.org/10.1115/1.2181180>.
  - [37] Diakunchak IS. Performance deterioration in industrial gas turbines. J Eng Gas Turb Power 1992;114:161. <http://dx.doi.org/10.1115/1.2906565>.